Ensemble deep learning optimization and medical image classification with convolutional neural networks

M. Poonguzhali [a], Niraj Upadhayaya [b], Sourabh Bhattacharya [c], Sunil Devidas Bobade [d], SHAIK MOHAMMAD RAFI[e], S.Ramkumar [f]

[a]Professor, Department of ECE, Narasu's Sarathy Institute of Technology, Poosaripatty post, Salem 636305, Tamilnadu. poonguzhali.m@nsit.edu.in,

[b]Professor (CSE) and Dean J B Institute of Engineering and Technology Moinabad, Hyderabad nirajup@gmail.com,

[c]Associate Professor Department of Management & Social ScienceHaldia Institute of Technology sourabhb82@gmail.com

[d]New Horizon Institute of Technology and Management, Thane, India 400615 Email: sunilbobade@nhitm.ac.in ORCID: 0000-0001-8650-2826,

[e]Professor in the department of computer science and engineering Sri Mittapalli college of engineering, Guntur Andhrapradesh 522233 mdrafi.527@gmail.com,

[f]Electronics and communication engineering Sri Sairam college of engineering, Bangalore. sram0829@gmail.com

Abstract

Innovative and effective medical image classification pipelines make extensive use of ensemble learning algorithms. The objective of ensemble learning is to improve the accuracy of predictions by combining diverse models or multiple forecasts. It is unknown whether and to what extent ensemble learning algorithms are advantageous in deep learning-based medical image classification pipelines. This paper proposes a scalable classification pipeline for testing the performance impact of augmenting, stacking, and bagging ensemble learning algorithms on medical image classification. The pipeline consists of nine deep convolution neural network topologies in addition to cutting-edge preprocessing and image enhancement techniques. We utilized four common medical imaging datasets of increasing complexity. In this study, we developed a method for classifying medical images that can be used repeatedly. Thus, we can examine the effects of Augmenting, Stacking, and Bagging on performance. The pipeline consists of nine deep convolution neural network architectures and cutting-edge image preprocessing and enhancement techniques. It was applied to four well-known medical imaging datasets of varying difficulty. Also examined were 12 pooling functions that combine multiple predictions. These functions ranged from simple statistical ones, such as unweighted averaging, to more complex ones, such as learning-based support vector machines. Based on our findings, Stacking achieved the highest performance increase with a 13 percent increase in F1 score. In addition to being applicable to single-model-based pipelines, augmentation has demonstrated up to a 4 percent improvement in capabilities..

Keywords: Convolutional Neural Network; Medical image classification, Ensemble Learning;

Number: 10.14704/nq.2022.20.7.NQ33423 **Neuro Quantology 2022; 20(7):3431-3442**

Overview

The field of automated medical image processing has experienced explosive growth in recent decades. Deep neural networks have become one of the most popular and widely used computer vision techniques. Deep convolutional neural network topologies are the foundation of this advancement. Despite their impressive predictive capabilities, the efficiency of these designs was comparable to that of doctors. Incorporating automated medical image analysis based on deep learning into clinical practise is a popular area of study at present. The sector medical image classification (MIC) attempts to assign a complete image to a particular category, such as a diagnosis or condition. The goal is to

employ these models as clinical decision support for physicians in order to improve diagnostic precision or automate time-consuming procedures. Recent research has demonstrated that ensemble learning algorithms are largely responsible for the effectiveness and accuracy of MIC systems. The main aim of the field of machine learning is to discover a hypothesis that maximizes ability for prediction of accuracy.

In any case, deciding the ideal speculation is troublesome, so a technique was created to consolidate different speculations into a more precise classifier that is nearer to the ideal speculation. With regards to profound convolutional brain organizations, speculations are addressed by altered cnn designs. Grouping procedure is hence portrayed as an infusion of models to upgrade forecast exactness. Profound group learning is the fuse of gathering learning procedures into a pipeline in light of profound learning. Current discoveries show that this procedure has been effectively carried out to work on the presentation and versatility of their MIC pipeline. Observationally, outfit learning-based pipelines will generally be unrivaled on the grounds that building different models has the advantage of joining their assets in zeroing in on unmistakable angles while making up for each model's specific shortcoming. It is obscure whether and how much outfit learning calculations are worthwhile in profound learning-based clinical picture grouping pipelines. Regardless of the way that the field and idea of summed up administered techniques are not novel, the impact of troupes learning strategies in profound learning-based order has not yet been comprehensively concentrated on in the writing. While various creators, for example, Ganaiea et al., have led broad examination on wide managed strategies, a couple of papers have started to investigate the profound group learning field.

Clinical consideration is stressed over people's prosperity. As of now, there is a colossal proportion of clinical data, yet it is essential that this data be utilized effectively to impel the clinical region. Notwithstanding the colossal measure of clinical data, there are at this point different issues: Medical data is varying, including maps, messages, accounts, magnets, etc; as a result of different equipment used, the idea of data moves basically; data presents fluctuating characteristics, after a few time and unequivocal events change; the law of the disorder doesn't have boundless propriety due to individual differences. There are different wild parts adding to the ascent of these difficulties. Clinical imaging is an essential piece of clinical data.

This survey begins with a preamble to the use of significant learning estimations in clinical picture assessment, then, explains the procedures of significant learning portrayal and division, and wraps up with a diagram of the more customary and contemporary standard association models. Then, at that point, we made sense of on the request and division of clinical pictures using significant getting, including fundus, CT/MRI tomography, ultrasound, and modernized pathology considering different imaging systems. It wraps up with a discussion of likely issues and a figure addressing things to come improvement of significant learning clinical imaging assessment.

Review of Literature

CNNs are convolutional neural networks that are profound multi-facet fake neural networks CNNs contain convolutional layers that permit the model to infer include maps by increasing the contribution with a learned piece. These component maps are then used to recognize designs, like nearby designs and edges. Since they can rapidly separate elements, they are especially successful for design acknowledgment in picture information examination. Furthermore, they have been shown to be especially exact in picture understanding, especially clinical imaging CNNs beat nonintrinsic highlights removed, for example, strategic relapse and backing vector machines, for organ and body part division. CNN-based CAD frameworks have been utilized successfully to identify cellular breakdown in the lungs, flu, and macular degeneration from X-beam and optical soundness tomography (OCT) pictures, separately . Late examination has presented a technique for AD founded on double tree complex wavelet change for highlight extraction and order by a feedforward neural organization. CNN plans, for example, GoogLeNet and ResNet have delivered amazing outcomes utilizing MRI imaging information to recognize solid, Alzheimer's sickness (AD), and gentle mental debilitation (MCI) cerebrums .

Using generative adversarial networks (GANs) is one more typical technique for improving imaging information. GANs produce new information that rival a discriminative whose work it is to characterize this new information as genuine or counterfeit (Goodfellow et al., 2014). Using generative networks that beat discriminative models, one can deliver fictitious information in view of the fundamental construction of genuine information (Wu et al., 2017). GANs have been used effectively in the field of clinical imaging for MRI and CT reproduction and unqualified blend (Wolterink et al., 2017; Yi et al., 2019).

Algorithms of Deep learning

Including deep learning for picture depiction is on the increase and a subject of progress. Convolutional neural association (CNN) is the most notable advancement among them. Since Krizhevsky et al. proposed AlexNet considering the CNN deep learning model in 2012 (5), which won the 2012 ImageNet picture depiction title, deep learning has detonated. Lin et al. presented the association in network (NIN) structure in 2013, which utilized generally normal pooling to diminish the bet of overfitting (6). GoogLeNet and VGGNet both updated the accuracy of the ImageNet dataset in 2014. (7,8). GoogLeNet has refreshed the introduction of the v2, v3, and v4 varieties (9-11). He et al. proposed the spatial pyramid pooling (SPP) model to work on the flexibility of information considering the injuries of CNN's great data size limits (12). With the deepening of the deep learning model, He et al. presented the holding up association ResNet as a reaction for the sensible issue of model defilement, and they keep on driving deep learning headway (13).

Five convolutional layers and three completely connected levels involved the AlexNet's eight-layer network engineering. Following every convolution in five convolutional layers, a greatest pooling is led to limit the amount of information. AlexNet acknowledges 227×227 pixels' feedback information. The 66257-highlight framework was in the long run submitted to the completely associated layer after five rounds of convolution and pooling methods. The 6th layer of the completely associated layer designs 4,098 convolution portions and a straight component esteem with a 4,097-size dropout. Following the last two layers, 1,000 float-type yield information are acquired as the last expectation result. AlexNet's slip-up rate in ImageNet was 15.2%, which was altogether higher than the second-set framework's blunder pace of 26.2%. Likewise, its enactment capability isn't sigmoid however ReLU, and it has been exhibited that the ReLU capability is more effective.

Process of segmentation

Deep learning research in semantic division is critical. With the quick improvement of deep learning development, endless astonishing semantic division neural networks emerge and continue to be state of the art in various division challenges. Since CNN's result in plan, people have begun to attempt various things with it for picture division. Despite the way that CNN can recognize photos of any size as data, it will lose a couple of nuances while pooling for feature extraction, as well as the space information of the information picture as a result of the organization's completely related layers close to the end. Therefore, CNN battles with sorting out which class explicit pixels have a spot with. Some division networks considering convolution still up in the air as deep learning advancement advances.

Long et al. proposed the completely convolutional network (FCN) (14) as the originator of semantic division networks. It replaces the gathering network VGG16's completely connected layers with convolutional layers while holding the spatial information of the part map and achieving pixel-level request. Finally, FCN restores the image by deconvolution and merging feature maps, and softmax gives the division result to each pixel. The FCN diminishes the amount of limits that ought to be arranged essentially by displacing the completely connected layer with thick relationship with a convolutional layer that is secretly related and shares loads. The FCN's display on the Pascal VOC 2012 datasets (15) has chipped away at by 20% over the past strategy, showing up at 62.2 percent of the mIOU. The component map is deconvolved after association. Skip affiliation is a method for directly utilizing shallow components that fluctuates from standard convolution, pooling, and various undertakings. U-Net uses the skip

affiliation joining framework to completely utilize the features of the encoder's down examining region to be used for up inspecting. This framework is applied to shallow part information across all scales to achieve a more refined decline influence.

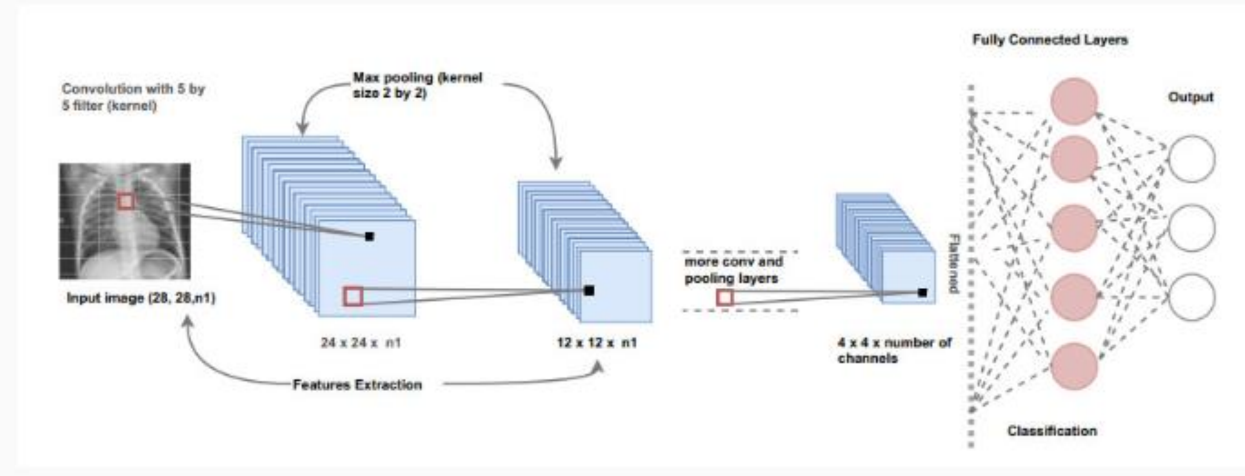

Figure 1 : Architecture of CNN Model

Ensemble machine learning

Ensemble learning is a conventional meta-way to deal with AI since it looks for the best expectation execution by consolidating the methodologies with the most elevated precision [22]. Exclusively, numerous AI calculations will be unable to deliver the best outcomes; thusly, consolidating the calculations joins the qualities of the model and further develops precision. The accompanying outline shows different Machine Learning calculations. It has been shown that the Ensemble learning technique for the expectation and classification of clinical pictures delivers improved results than utilizing a solitary classifier. Scarcely any endeavors on Convolutional Neural Networks (CNN) for break finding were referenced in the audits of commended man-made reasoning frameworks for distinguishing body cracks [24].

Also, the creators noticed that stacking utilizing Random Forest and Support Vector calculations, related to neural networks, was generally predominant. Utilizing otoendoscopy pictures, [23] made an Ensemble deep learning application for ear problems. The typical exactness for the five-crease cross-approval using learning models in view of ResNet101 and Inception-V3 is 93.67 percent, demonstrating great execution. Furthermore, another creator [26] built a three-layered bone model framework that utilizes x-beam photos of the distal lower arm and convolutional neural networks. The structure for deep learning is utilized to gauge and produce an exceptionally precise three-layered model of bones. The result shows the precision of CNN's evaluation to restrict openness to PC tomography gadgets and expenses. All in all, the utilization of Ensemble strategies to clinical imaging can be sought after with life as the exactness recorded is fundamentally higher than that of single classifiers or traditional methodologies.

There are three extraordinary kinds of ensemble learning, including firing, stacking, and supporting. The terminating strategy is stressed over having various options on different instances of the identical dataset and averaging the estimate, however the stacking method is stressed over fitting various kinds of models to comparative data while using a third sort of model to get to know the joined assumptions. Helping is the unique extension of ensemble people that right the previous measure made by various models before working out the mean of the conjectures.

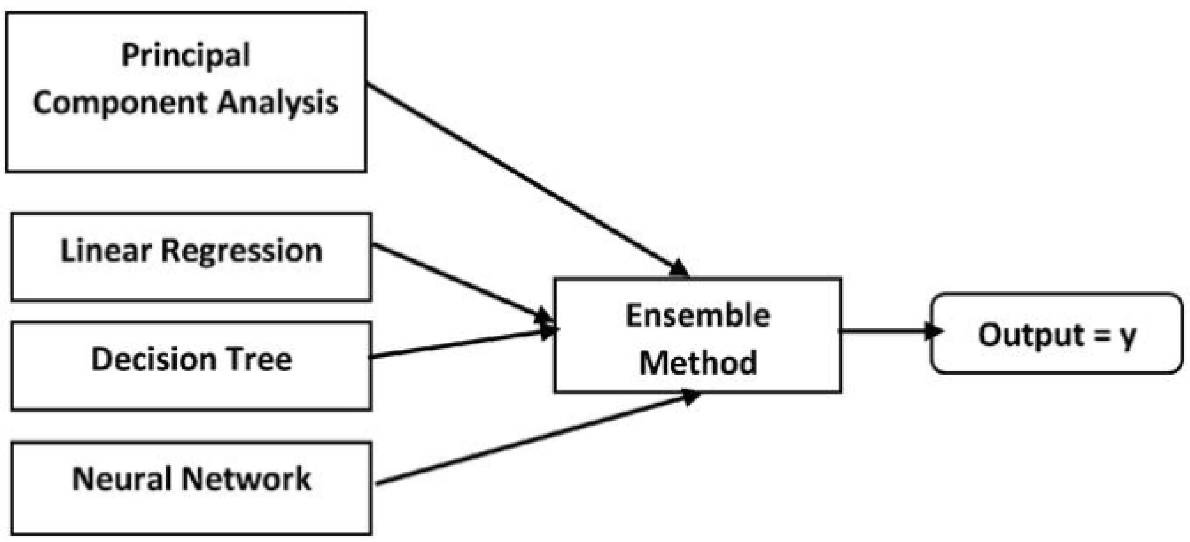

Figure2: Combning multiple models of Ensemble machine learning

An ensemble philosophy for mentioning bone breaks using several CNN is introduced. The creators were energized by the need to help the crisis considered bone break for a faster reaction than the standard procedure of going through X-transmits and in this manner sending the outcomes to experts for better understandings. The method can be wide considering the way that nothing major can happen until the result is uncovered. The producer proposes a better way than manage further encourage the cycles attracted with completing this basic piece of a clinical crisis. The evaluation applies ensemble AI system using CNN to sort the photographs of bone breaks including a stacking methodology for solid and red hot depiction. The outcome shows that the ensemble approach is more dependable and produces something heartier than the suppliers' manual works [32]. The solicitation for shoulder pictures using X-bar pictures utilizing deep learning ensemble models for end, with information amassed from engaging resounding imaging and figured tomography X-support point pictures. The goal of this study is to arrange photos including man-made remembering to see their condition. The work utilizes 26 deep learning models and outside muscle radiograph datasets associated with ensemble learning models to analyze shoulder breaks. The social affair of 28 things was driven, and the general exactness was settled utilizing Cohen's kappa. Utilizing an ensemble of ResNet34, DenseNet169, DenseNet201, and a sub-ensemble of several convolution networks [33,34-69], the best score was 0.6942.

Approaches of Ensemble

The base students (where the information reliance remains) are started progressively in the nonstop strategy. Likewise, all ensuing information in the base level are reliant upon the past information, and to get an exhibition examination of the framework, the erroneously marked information are weight-changed. This type of examination is delineated by means of the supporting strategy. The equal philosophy guarantees that the student is started in equal, that there is no information reliance, and that all information are created freely. The stacking approach [36] is a superb representation of this model.

The homogeneous ensemble approach can be applied to an enormous number of datasets because of the utilization of a combination of indistinguishable classifiers. The dataset is dependably unmistakable for every classifier, and the model performs well subsequent to gathering results for every classifier model. The element determination method is no different for all preparing information types. The greatest disadvantage of this kind of model is its powerful computational expense. The most well-known type of this plan is the sacking and helping strategy. Conversely, the heterogeneous ensemble strategy blends different classifiers,

every one of which is based on similar information. These sorts of strategies are used for little datasets, and the component determination process for a similar preparation dataset is unmistakable. Stacking is an illustration of this kind of classifier.

Classification of ensemble approach

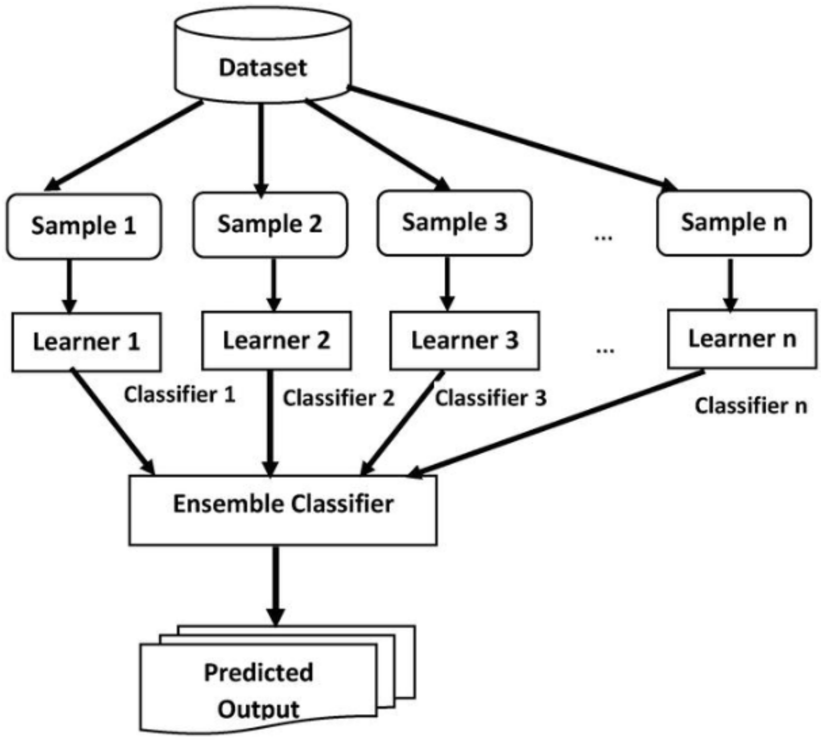

Figure 3: Framework for prediction and classification

Research Methodology

The reason for this system is to improve the image information (highlights) by smothering undesired twists and upgrading key picture viewpoints, so our Computer Vision models can work with this improved information. Identification of an objective: Detection alludes to the confinement of an item, which includes portioning the picture and identifying the area of the objective article. Extraction of highlights and Training: This is a crucial stage where factual or deep learning approaches are utilized to find the picture's most fascinating examples, includes that might be special to a specific class, and which will thusly help the model in separating across classes. The cycle through which a model procures highlights from a dataset is known as model preparation. Grouping of the item: Using a reasonable characterization calculation that looks at the image examples to the objective examples, this stage orders recognized things into foreordained classes.

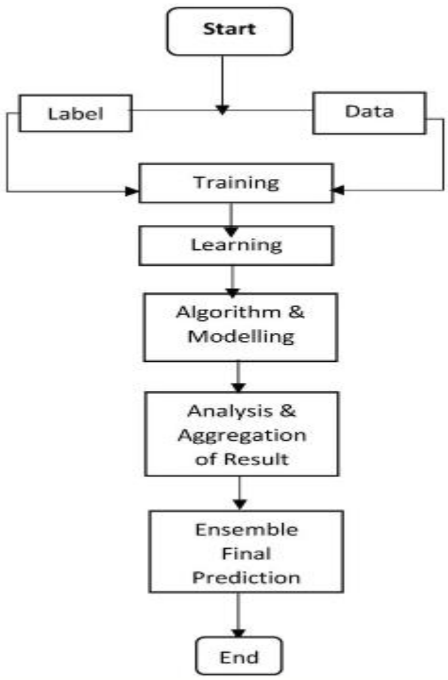

Figure 4: Framework

This review proposes an ensemble AI application procedure for the request and assumption for clinical pictures. The survey bases on the usage of different AI estimations as a joined model to achieve additionally created results due to the models' assortment. The photos will be pre-dealt with, improved, dealt with to the classifier for planning and testing, and a while later the expected result not permanently set up.

Results

This part summarizes and examinations the exploratory results used to survey the proposed FS improvement strategy. We start by standing apart our framework from other meta-heuristic streamlining strategies. Following this, the help vector with machining (SVM) classifiers were analyzed. Additionally, this is trailed by an evaluation with other existing clinical imaging demand structures utilizing different exchange learning models, as DenseNet, MobileNet, and the ensemble model. At this point open for evaluation are review, accuracy, F1-score, changed accuracy, and exactness. At long last, it was stood apart from techniques actually scattered.

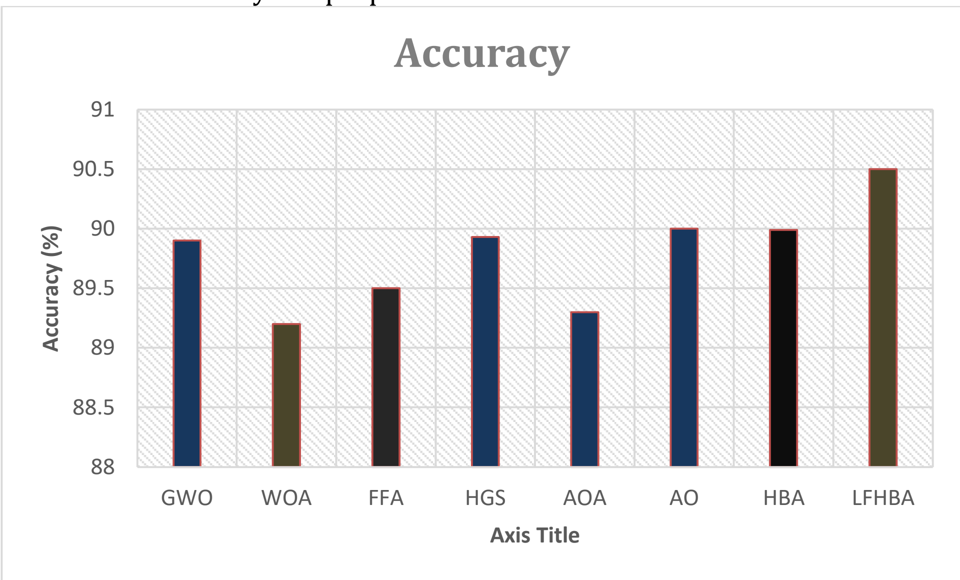

Figure 5 : Graph of Accuracy

These upgrade estimations are surveyed using various estimations to handle complex numerical improvement issues. On account of the whimsies of execution assessment issues, the parts of both datasets were diminished to 20 sections and the number of accentuations was set to 1000 for all starters. The more noticeable the amount of search trained professionals, the more conspicuous the likelihood that the overall ideal will be found. The model size for all tests is fixed at 50. Decrease the amount of search experts to handle the over-the-top issue.

Conclusion

Stacking, which applies pooling abilities on top of various deep convolutional neural organization plans, was the ensemble learning system with the best show. Different cutting edge clinical picture portrayal pipelines uses a Stacking-based pipeline development to overhaul execution by combining novel plans or differently pre-arranged models. Utilizing the gauge information of various procedures prompts additionally created derivation quality and a decrease in inclination or bungle. Besides, that is what our evaluation revealed, as per F1-score results, clear pooling limits, for example, averaging by Mean or a Soft Majority Vote accomplish a relatively solid or essentially more grounded execution gain than more fantastic pooling limits, for example, Support Vector Machines or Logical Regressions. In any case, as per the possible results of Accuracy, the more confused pooling skills got higher scores. This shows that the discipline procedure of the models that were prepared with a class-

weighted mishap limit in our primers is as of now used by more clear pooling skills. Accordingly, the consequences of our major abilities to pool keep on impelling class-changed assessments, for example, F1-score and Sensitivity. Then again, more stunning pooling limits with a particular status process zeroed in on dealing with the complete number of ensured cases, including genuine negatives, which accomplished higher scores for conflicting assessments like Accuracy. essentially, other persistent assessments that explored the effect of Stacking support our speculation that Stacking can work on the demonstration of individual deep convolutional neural association models by as much as 11%.

References

1. A. Ahmad, "Breast cancer statistics: recent trends," *Advances in Experimental Medicine & Biology*, pp. 1–7, 2019.
2. M. M. A. Eid, A. N. Z. Rashed, A. A.-M. Bulbul, and E. Podder, "Mono-rectangular core photonic crystal fiber (mrc-pcf) for skin and blood cancer detection," *Plasmonics*, vol. 16, no. 3, pp. 717–727, 2021.
3. B. Jin, Y. Zhao, and Y. Liang, "Internet of things medical image detection and pediatric renal failure dialysis complicated with respiratory tract infection," *Microprocessors and Microsystems*, vol. 83, Article ID 104016, 2021.
4. A. Pouttu, F. Burkhardt, C. Patachia et al., "6G white paper on validation and trials for verticals towards 2030's," *6G Research Visions*, vol. 4, 2020.
5. W. Wang, F. Liu, X. Zhi, T. Zhang, and C. Huang, "An integrated deep learning algorithm for detecting lung nodules with low-dose ct and its application in 6g-enabled internet of medical things," *IEEE Internet of Things Journal*, vol. 8, no. 7, pp. 5274–5284, 2021.
6. A. G. Howard, M. Zhu, B. Chen et al., "MobileNets: Efficient Convolutional Neural Networks for mobile Vision Applications," 2017, https://arxiv.org/pdf/1704.04861.
7. D. D. A. Rodrigues, R. F. Ivo, S. C. Satapathy, S. Wang, J. Hemanth, and P. P. R. Filho, "A new approach for classification skin lesion based on transfer learning, deep learning, and iot system," *Pattern Recognition Letters*, vol. 136, pp. 8–15, 2020.
8. A. Mabrouk, R. P. D. Redondo, and M. Kayed, "Seopinion: summarization and exploration of opinion from e-commerce websites," *Sensors*, vol. 21, no. 2, p. 636, 2021.
9. G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 4700–4708, Hawaii, HW, USA, July 2017
10. X. Zhang, X. Zhou, M. Lin, and J. Sun, "Shufflenet: an extremely efficient convolutional neural network for mobile devices," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 6848–6856, Salt Lake City, UT, USA, June 2018.
11. B. Zoph, V. Vasudevan, J. Shlens, and Q. V. Le, "Learning transferable architectures for scalable image recognition," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 8697–8710, Salt Lake City, UT, USA, June 2018.
12. M. Tan and Q. Le, "Efficientnet: rethinking model scaling for convolutional neural networks," in *Proceedings of the International Conference on Machine Learning. PMLR*, pp. 6105–6114, California, CA, USA, June 2019.
13. A. Ignatov, A. Romero, H. Kim, and R. Timofte, "Real-time video super-resolution on smartphones with deep learning, mobile ai 2021 challenge: Report," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 2535–2544, Nashville, TN, USA, June 2021.
14. J. Liu, N. Inkawhich, O. Nina, and R. Timofte, "Ntire 2021 multi-modal aerial view object classification challenge," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 588–595, Nashville, TN, USA, June 2021.
15. C. Wen, X. Yang, K. Zhang, and J. Zhang, "Improved loss function for image classification," *Computational Intelligence*

and Neuroscience, vol. 2021, Article ID 6660961, 8 pages, 2021.

16. A. Farki, Z. Salekshahrezaee, A. M. Tofigh, R. Ghanavati, B. Arandian, and A. Chapnevis, “COVID-19 diagnosis using capsule network and fuzzy C-means and mayfly optimization algorithm,” *BioMed Research International*, vol. 2021, Article ID 6660961, 11 pages, 2021
17. W. Wang, Y. Hu, Y. Luo, and X. Wang, “Medical image classification based on information interaction perception mechanism,” *Computational Intelligence and Neuroscience*, vol. 2021, Article ID 8429899, 12 pages, 2021.
18. Z. Rahman, M. S. Hossain, M. R. Islam, M. M. Hasan, and R. A. Hridhee, “An approach for multiclass skin lesion classification based on ensemble learning,” *Informatics in Medicine Unlocked*, vol. 25, Article ID 100659, 2021.
19. H. Adel, A. Dahou, A. Mabrouk et al., “Improving crisis events detection using distilbert with hunger games search algorithm,” *Mathematics*, vol. 10, no. 3, p. 447, 2022.
20. D. Gupta, S. Sundaram, A. Khanna, A. Ella Hassanien, and V. H. C. De Albuquerque, “Improved diagnosis of Parkinson’s disease using optimized crow search algorithm,” *Computers & Electrical Engineering*, vol. 68, pp. 412–424, 2018.
21. S. V. N. Sreenivasu, S. Gomathi, M. Jogendra Kumar, Lavanya Prathap, Abhishek Madduri, Khalid M. A. Almutairi, Wadi B. Alonazi, D. Kali, S. Arockia Jayadhas, "Dense Convolutional Neural Network for Detection of Cancer from CT Images", BioMed Research International, vol. 2022, Article ID 1293548, 8 pages, 2022.
22. Mukesh Soni, Ihtiram Raza Khan, K. Suresh Babu, Syed Nasrullah, Abhishek Madduri, Saima Ahmed Rahin, "Light Weighted Healthcare CNN Model to Detect Prostate Cancer on Multiparametric MRI", Computational Intelligence and Neuroscience, vol. 2022, Article ID 5497120, 11 pages, 2022.
23. Mehraj, Haider, D. Jayadevappa, Sulaima Lebbe Abdul Haleem, Rehana Parveen, Abhishek Madduri, Maruthi Rohit Ayyagari, and Dharmesh Dhabliya. "Protection motivation theory using multi-factor authentication for providing security over social networking sites." Pattern Recognition Letters 152 (2021): 218-224.
24. Abhishek Madduri. "Human Gait Recognition using Discrete Wavelet and Discrete Cosine and Transformation Based Features." International Journal of Computer Trends and Technology, vol. 69, no. 6, June. 2021, pp.22-27.
25. Abhishek Madduri. Content based Image Retrieval System using Local Feature Extraction Techniques. International Journal of Computer Applications 183(20):16-20, August 2021.
26. Sharma, D. K., Chakravarthi, D. S., Boddu, R. S. K., Madduri, A., Ayyagari, M. R., & Khaja Mohiddin, M. (2023). Effectiveness of Machine Learning Technology in Detecting Patterns of Certain Diseases Within Patient Electronic Healthcare Records. In Proceedings of Second International Conference in Mechanical and Energy Technology (pp. 73-81). Springer, SingaporeIn Proceedings of Second International Conference in Mechanical and Energy Technology (pp. 73-81). Springer, Singapore
27. Rathore, M. S., Poongodi, M., Saurabh, P., Lilhore, U. K., Bourouis, S., Alhakami, W., ... & Hamdi, M. (2022). A novel trust-based security and privacy model for Internet of Vehicles using encryption and steganography. *Computers and Electrical Engineering*, *102*, 108205.
28. Poongodi, M., Bourouis, S., Ahmed, A. N., Vijayaragavan, M., Venkatesan, K. G. S., Alhakami, W., & Hamdi, M. (2022). A Novel Secured Multi-Access Edge Computing based VANET with Neuro fuzzy systems based Blockchain Framework. *Computer Communications*.
29. Ramesh, T. R., Lilhore, U. K., Poongodi, M., Simaiya, S., Kaur, A., & Hamdi, M. (2022). PREDICTIVE ANALYSIS OF HEART DISEASES WITH MACHINE LEARNING APPROACHES. *Malaysian Journal of Computer Science*, 132-148.
30. Poongodi, M., Malviya, M., Hamdi, M., Vijayakumar, V., Mohammed, M. A., Rauf, H. T., & Al-Dhlan, K. A. (2022). 5G based

Blockchain network for authentic and ethical keyword search engine. *IET Commun.*, *16*(5), 442-448.

31. Poongodi, M., Malviya, M., Kumar, C., Hamdi, M., Vijayakumar, V., Nebhen, J., & Alyamani, H. (2022). New York City taxi trip duration prediction using MLP and XGBoost. *International Journal of System Assurance Engineering and Management*, *13*(1), 16-27.
32. Poongodi, M., Hamdi, M., & Wang, H. (2022). Image and audio caps: automated captioning of background sounds and images using deep learning. *Multimedia Systems*, 1-9.
33. Poongodi, M., Hamdi, M., Gao, J., & Rauf, H. T. (2021, December). A Novel Security Mechanism of 6G for IMD using Authentication and Key Agreement Scheme. In *2021 IEEE Globecom Workshops (GC Wkshps)* (pp. 1-6). IEEE.
34. Ramesh, T. R., Vijayaragavan, M., Poongodi, M., Hamdi, M., Wang, H., & Bourouis, S. (2022). Peer-to-peer trust management in intelligent transportation system: An Aumann's agreement theorem based approach. *ICT Express*.
35. Hamdi, M., Bourouis, S., Rastislav, K., & Mohmed, F. (2022). Evaluation of Neuro Image for the Diagnosis of Alzhimer's Disease Using Deep Learning Neural Network. *Frontiers in Public Health*, 35.
36. Poongodi, M., Hamdi, M., Malviya, M., Sharma, A., Dhiman, G., & Vimal, S. (2022). Diagnosis and combating COVID-19 using wearable Oura smart ring with deep learning methods. *Personal and ubiquitous computing*, *26*(1), 25-35.
37. Sahoo, S. K., Mudligiriyappa, N., Algethami, A. A., Manoharan, P., Hamdi, M., & Raahemifar, K. (2022). Intelligent Trust-Based Utility and Reusability Model: Enhanced Security Using Unmanned Aerial Vehicles on Sensor Nodes. *Applied Sciences*, *12*(3), 1317.
38. Muniyappan, A., Sundarappan, B., Manoharan, P., Hamdi, M., Raahemifar, K., Bourouis, S., & Varadarajan, V. (2022). Stability and numerical solutions of second wave mathematical modeling on covid-19 and omicron outbreak strategy of pandemic: Analytical and error analysis of approximate series solutions by using hpm. *Mathematics*, *10*(3), 343.
39. Rawal, B. S., Manogaran, G., & Poongodi, M. (2022). Implementing and Leveraging Blockchain Programming.
40. Bourouis, S., Band, S. S., Mosavi, A., Agrawal, S., & Hamdi, M. (2022). Meta-Heuristic Algorithm-Tuned Neural Network for Breast Cancer Diagnosis Using Ultrasound Images. *Frontiers in Oncology*, *12*, 834028.
41. Lilhore, U. K., Poongodi, M., Kaur, A., Simaiya, S., Algarni, A. D., Elmannai, H., ... & Hamdi, M. (2022). Hybrid Model for Detection of Cervical Cancer Using Causal Analysis and Machine Learning Techniques. *Computational and Mathematical Methods in Medicine*, *2022*.
42. Dhiman, P., Kukreja, V., Manoharan, P., Kaur, A., Kamruzzaman, M. M., Dhaou, I. B., & Iwendi, C. (2022). A Novel Deep Learning Model for Detection of Severity Level of the Disease in Citrus Fruits. *Electronics*, *11*(3), 495.
43. Dhanaraj, R. K., Ramakrishnan, V., Poongodi, M., Krishnasamy, L., Hamdi, M., Kotecha, K., & Vijayakumar, V. (2021). Random Forest Bagging and X-Means Clustered Antipattern Detection from SQL Query Log for Accessing Secure Mobile Data. *Wireless Communications and Mobile Computing*, *2021*.
44. Maurya, S., Joseph, S., Asokan, A., Algethami, A. A., Hamdi, M., & Rauf, H. T. (2021). Federated transfer learning for authentication and privacy preservation using novel supportive twin delayed DDPG (S-TD3) algorithm for IIoT. *Sensors*, *21*(23), 7793.
45. Poongodi, M., Nguyen, T. N., Hamdi, M., & Cengiz, K. (2021). Global cryptocurrency trend prediction using social media. *Information Processing & Management*, *58*(6), 102708.
46. Poongodi, M., Sharma, A., Hamdi, M., Maode, M., & Chilamkurti, N. (2021). Smart healthcare in smart cities: wireless patient monitoring system using IoT. *The Journal of Supercomputing*, *77*(11), 12230-12255.
47. Rawal, B. S., Manogaran, G., & Hamdi, M. (2021). Multi-Tier Stack of Block Chain with Proxy Re-Encryption Method Scheme on the Internet of Things Platform. *ACM Transactions on Internet Technology (TOIT)*, *22*(2), 1-20.
48. Poongodi, M., Malviya, M., Hamdi, M., Rauf, H. T., Kadry, S., & Thinnukool, O. (2021). The

recent technologies to curb the second-wave of COVID-19 pandemic. *Ieee Access*, *9*, 97906-97928.
49. Rawal, B. S., Manogaran, G., Singh, R., Poongodi, M., & Hamdi, M. (2021, June). Network augmentation by dynamically splitting the switching function in SDN. In *2021 IEEE International Conference on Communications Workshops (ICC Workshops)* (pp. 1-6). IEEE.
50. Poongodi, M., Hamdi, M., Varadarajan, V., Rawal, B. S., & Maode, M. (2020, July). Building an authentic and ethical keyword search by applying decentralised (Blockchain) verification. In *IEEE INFOCOM 2020-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)* (pp. 746-753). IEEE.
51. Poongodi, M., Vijayakumar, V., Al-Turjman, F., Hamdi, M., & Ma, M. (2019). Intrusion prevention system for DDoS attack on VANET with reCAPTCHA controller using information based metrics. *IEEE Access*, *7*, 158481-158491.
52. Poongodi, M., Hamdi, M., Sharma, A., Ma, M., & Singh, P. K. (2019). DDoS detection mechanism using trust-based evaluation system in VANET. *IEEE Access*, *7*, 183532-183544.
53. M. M. Kamruzzaman, ""New Opportunities, Challenges, and Applications of Edge-AI for Connected Healthcare in Smart Cities,"" 2021 IEEE Globecom Workshops (GC Wkshps), 2021, pp. 1-6, doi: 10.1109/GCWkshps52748.2021.9682055."
54. Md Selim Hossain, MM Kamruzzaman, Shuvo Sen, Mir Mohammad Azad, Mohammad Sarwar Hossain Mollah, Hexahedron core with sensor based photonic crystal fiber: An approach of design and performance analysis," Sensing and Bio-Sensing Research, 32, 100426
55. Mingju Chen, Xiaofeng Han, Hua Zhang, Guojun Lin, M.M. Kamruzzaman, Quality-guided key frames selection from video stream based on object detection, Journal of Visual Communication and Image Representation, Volume 65, 2019, 102678, ISSN 1047-3203
56. M. M. Kamruzzaman: Performance of Decode and Forward MIMO Relaying using STBC for Wireless Uplink. JNW 9(12): 3200-3206 (2014)
57. M. M. Kamruzzaman, "Performance of Turbo Coded Vertical Bell Laboratories Layered Space Time Multiple Input Multiple Output system," Computer and Information Technology (ICCIT), 2013 16th International Conference on, Khulna, 2014, pp. 455-459.
58. Yan Zhang, M. M. Kamruzzaman, and Lu Feng "Complex System of Vertical Baduanjin Lifting Motion Sensing Recognition under the Background of Big Data," Complexity, vol. 2021, Article ID 6690606, 10 pages, 2021. https://doi.org/10.1155/2021/6690606
59. Md Hossain , MM Kamruzzaman , Shuvo Sen, Mir Mohammad Azad, Mohammad Sarwar Hossain Mollah , Hexahedron Core with Sensor Based Photonic Crystal Fiber, 2021
60. Md Nazirul Islam Sarker, Md Lamiur Raihan, Yang Peng, Tahmina Chumky, MM Kamruzzaman, Roger C Shouse, Huh Chang Deog, "COVID-19: Access to Information, Health Service, Daily Life Facility and Risk Perception of Foreigners during Coronavirus pandemic in South Korea," Archives of Medical Science, 2021, https://doi.org/10.5114/aoms/141164
61. Y. Shi, S. Wang, S. Zhou and M. M. Kamruzzaman. (2020). Study on Modeling Method of Forest Tree Image Recognition Based on CCD and Theodolite. IEEE Access, vol. 8, pp. 159067-159076, 2020, doi: 10.1109/ACCESS.2020.3018180
62. Guobin Chen, Zhiyong Jiang, M.M. Kamruzzaman. (2020). Radar remote sensing image retrieval algorithm based on improved Sobel operator, Journal of Visual Communication and Image Representation, Volume 71, 2020, 102720, ISSN 1047-3203 https://doi.org/10.1016/j.jvcir.2019.102720.
63. Yuanjin Xu, Ming Wei, M.M. Kamruzzaman, Inter/intra-category discriminative features for aerial image classification: A quality-aware selection model,Future Generation Computer Systems,Volume 119,2021,Pages 77-83,ISSN 0167-

739X,https://doi.org/10.1016/j.future.2020.11.015.

64. Xing Li, Junpei Zhong, M.M. Kamruzzaman, “Complicated robot activity recognition by quality-aware deep reinforcement learning”, Future Generation Computer Systems,Volume 117, 2021, Pages 480-485.
65. Bin Yuan, M. M. Kamruzzaman, Shaonan Shan, "Application of Motion Sensor Based on Neural Network in Basketball Technology and Physical Fitness Evaluation System", Wireless Communications and Mobile Computing, vol. 2021, Article ID 5562954, 11 pages, 2021. https://doi.org/10.1155/2021/5562954
66. Chi, Z., Jiang, Z., Kamruzzaman, M.M. et al. Adaptive momentum-based optimization to train deep neural network for simulating the static stability of the composite structure. Engineering with Computers (2021). https://doi.org/10.1007/s00366-021-01335-5
67. Omarov, B., Narynov, S., Zhumanov, Z., Gumar, A., & Khassanova, M. (2022). State-of-the-art violence detection techniques in video surveillance security systems: a systematic review. PeerJ Computer Science, 8, e920.
68. 2. Tursynova, A., & Omarov, B. (2021, November). 3D U-Net for brain stroke lesion segmentation on ISLES 2018 dataset. In 2021 16th International Conference on Electronics Computer and Computation (ICECCO) (pp. 1-4). IEEE.
69. 3. Omarov, B., Narynov, S., Zhumanov, Z., Gumar, A., & Khassanova, M. (2022). A Skeleton-based Approach for Campus Violence Detection. CMC-COMPUTERS MATERIALS & CONTINUA, 72(1), 315-331.